Trust-based local and social recommendation

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Context

Collaborative Filtering Recommender Systems

- Data management
  - → Where are the data?
  - → Privacy
- Architecture
  - → Data decentralization
  - → P2P

Recommender System purely local

⇒ No global knowledge on ratings

⇒ User-centric data management

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Brief state of the art

Trust-based Recommender Systems

- MoleTrust [Massa2007]
  - → trust propagation
- RandomWalk [Jamali2009]
  - → purely local
- TrustWalker [Jamali2009]
  - → default scores based on item similarity

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Communication

Solely based on links in the social network

- No new link in the social network
- Trust and similarity weight scores
- Only friends may share data

P2P style communication

- 1 peer = 1 user (*aka* actor)
- 1 link = 1 explicit social link

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Proposition

Predict scores through the social network

- If there is a rating on the item, return it
- Otherwise ask friends
- Who will ask their friends
- ...

$\rightarrow$ Up to depth k

~~Trust propagation~~ $\Rightarrow$ Score propagation

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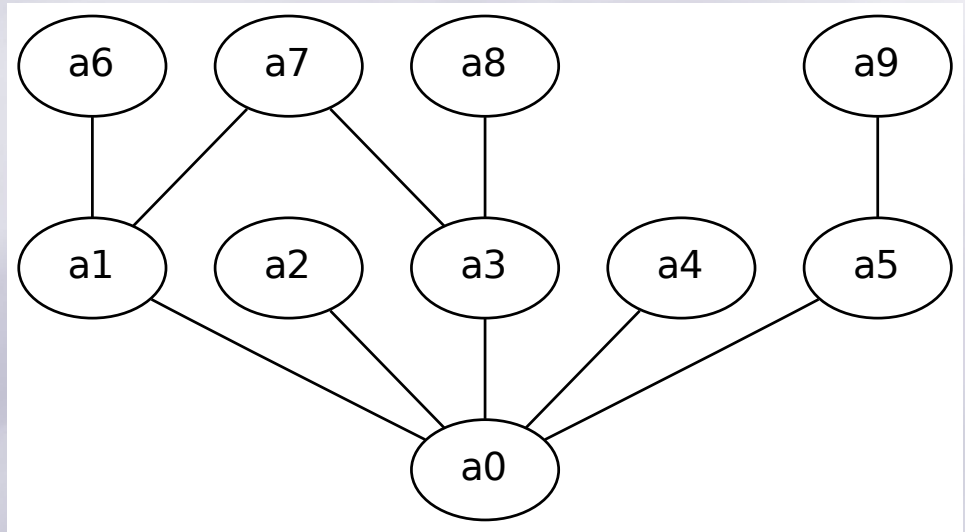
Example

a0	a1	a2	a3	a4	a5	a6	a7	a8	a9
X	0.2	$\perp$	$\perp$	0.8	$\perp$	0.6	0.9	0.5	0.1

(a) Actors' ratings on item i_0



(b) Social network

Figure : Social network and ratings example centered around a_0

Score propagation example

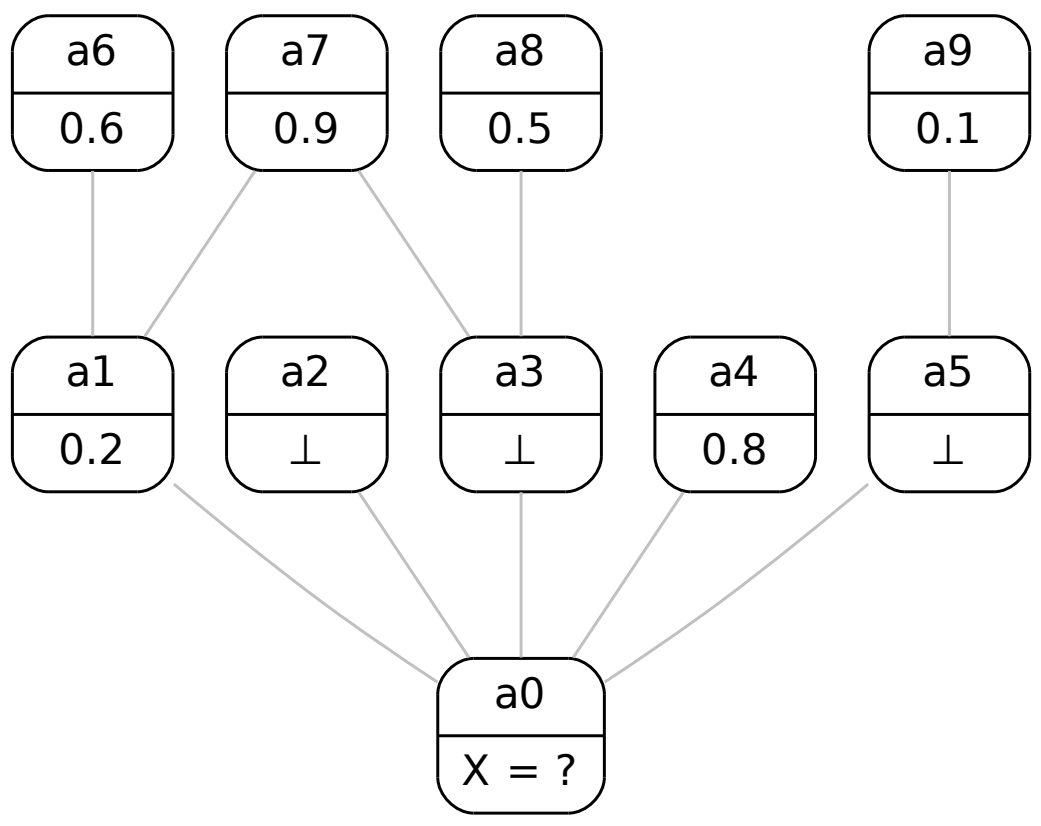
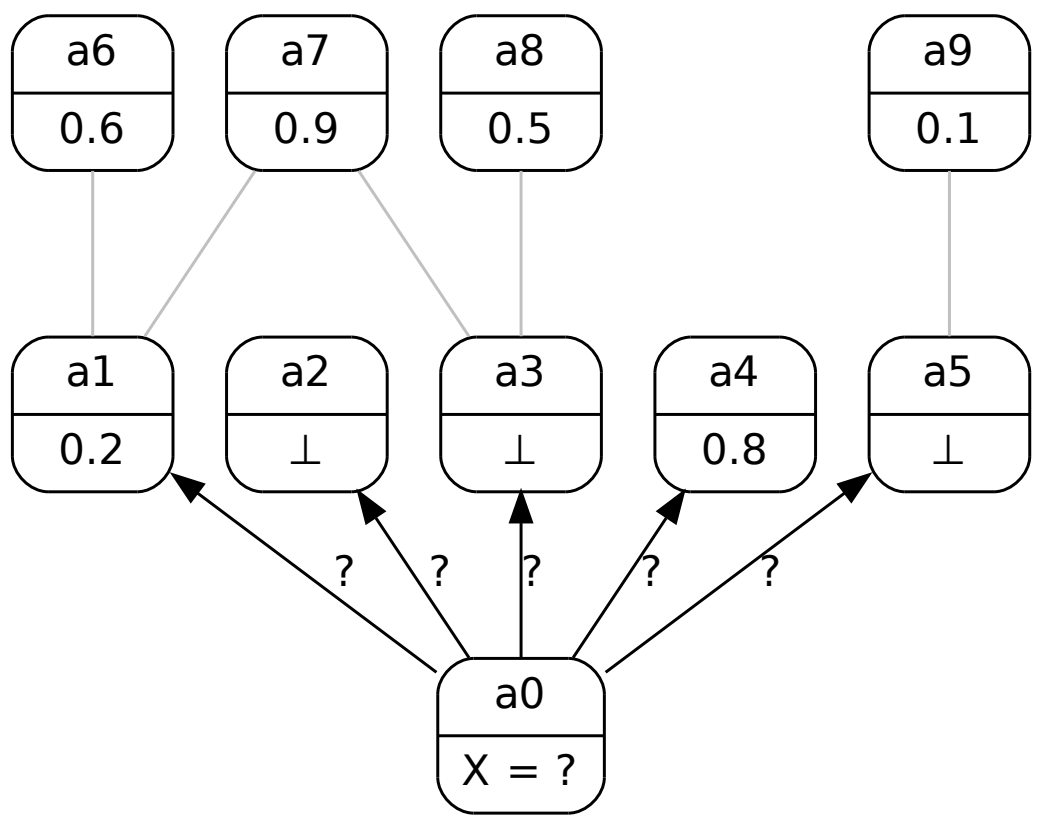


Figure : $k-$Depth Social Scoring Example with $k = 2$

Score propagation example



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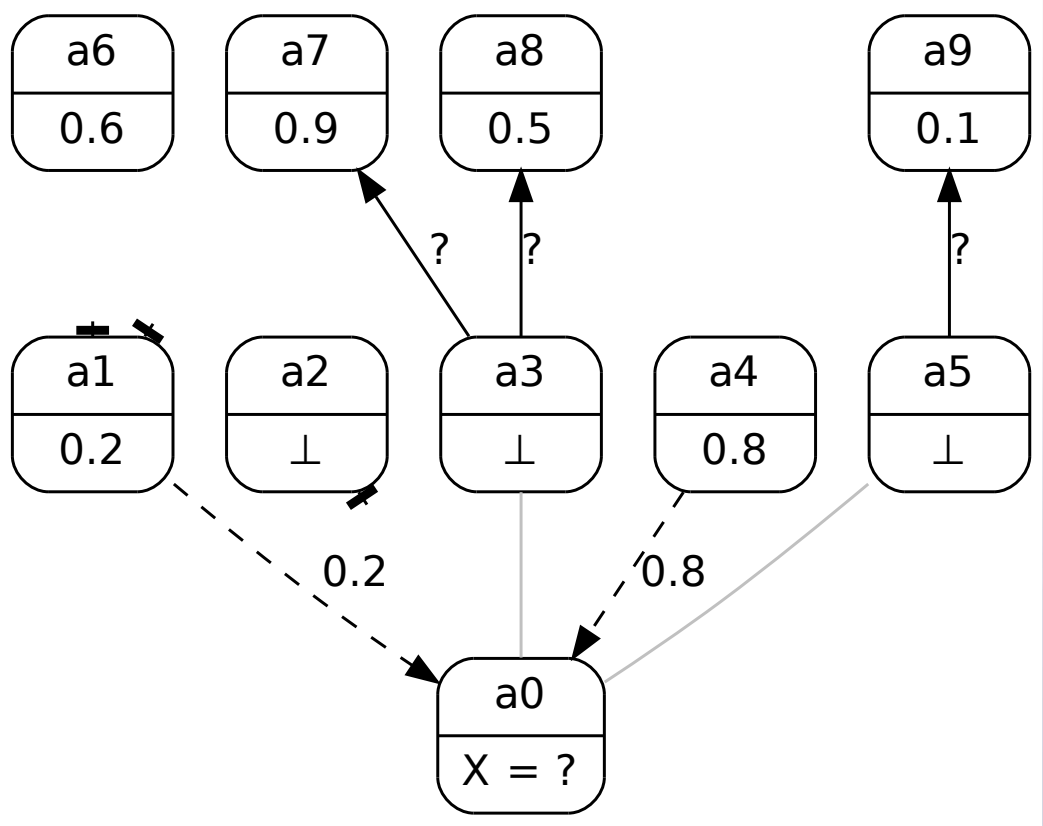

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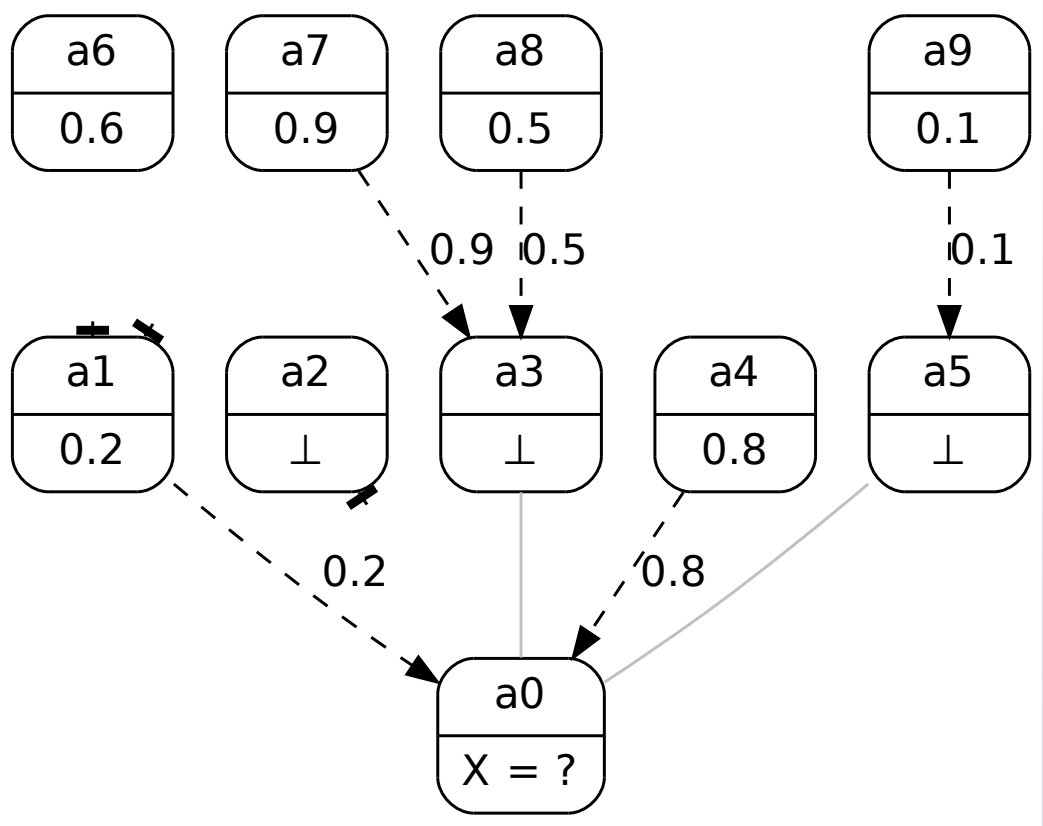

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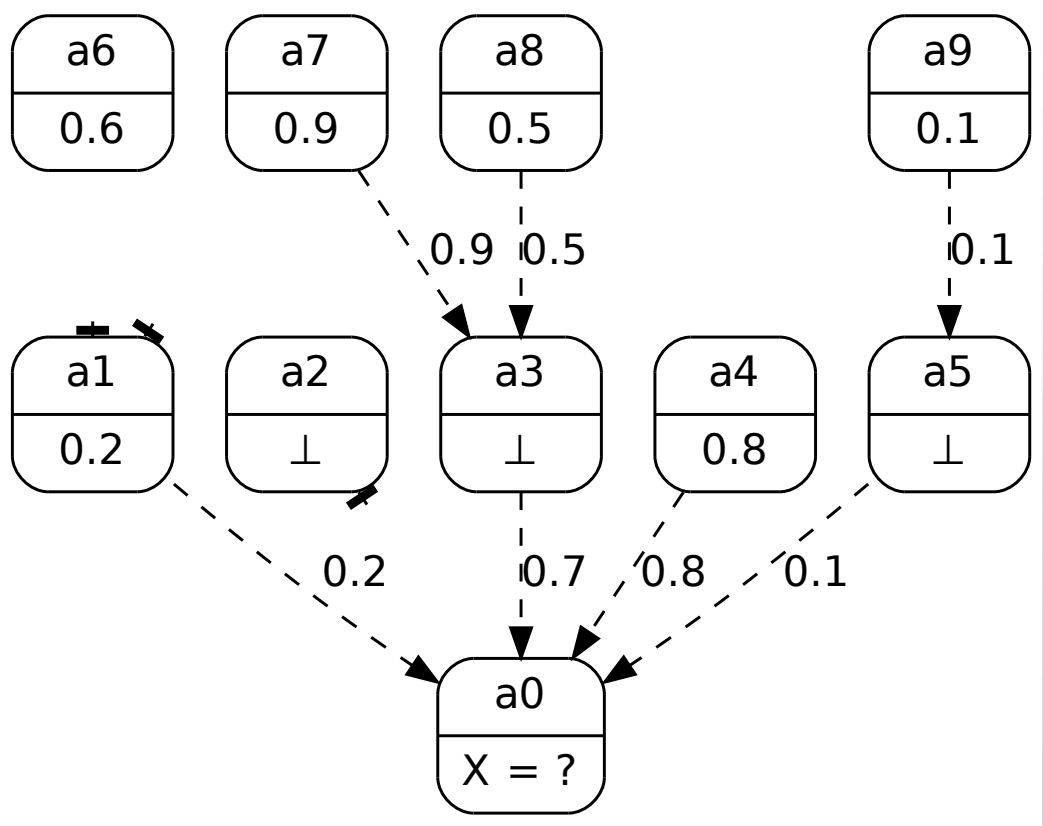

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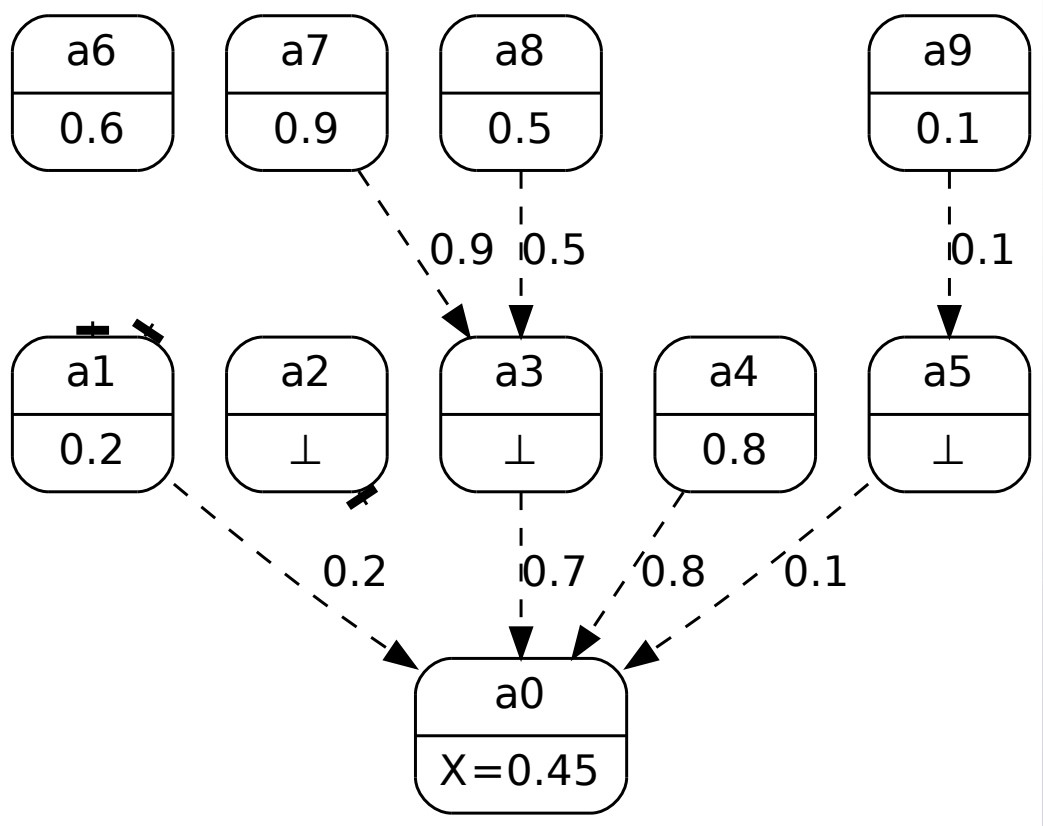

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Algorithm

$$\mathcal{F}^k_{a,i,\omega} = \{f \in F_a | s_k(f,i) \neq \perp \wedge \omega_{a,f} \neq 0\} \quad (1)$$

$$s_k(a,i) = \begin{cases} r_{a,i} & \text{if } \exists r_{a,i} \\ \dfrac{\sum_{f \in \mathcal{F}^{k-1}_{a,i,\omega}} \omega_{a,f} \times s_{k-1}(f,i)}{\sum_{f \in \mathcal{F}^{k-1}_{a,i,\omega}} \omega_{a,f}} & \text{if } \nexists r_{a,i} \wedge \mathcal{F}^{k-1}_{a,i,\omega} \neq \emptyset \\ default(a,i) & \text{otherwise} \end{cases} \quad (2)$$

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ω coefficient

- Trust
  - $\rightarrow$ Defined by actors on friends
- Correlation (*aka* similarity)
  - $\rightarrow$ Computed by the system between friends
- Confidence
  - $\rightarrow$ On the prediction accuracy
  - $\rightarrow$ Propagated with scores
  - $\rightarrow$ Recomputed by each actor

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Default score

If no score computed, return (or not) a default score

- Improve coverage on sparse datasets
- Add some randomness

Default score computation:

- Local strategy: $\overline{r_a}$
- Anonymous strategy: $\overline{r_i}$

$$P(default(a, i) \neq \perp) = P_{default}$$

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CoTCoDepth

Confident Trust Correlative $k-$Depth Social Scorer

Propagation up to $k = 3$ in the social network:

- CoTCoD3: $default(a, i) = \perp$
- CoTCoD3$_a$: $default(a, i) = \overline{r_a}$
- CoTCoD3$_{ia}$: $default(a, i) = \begin{cases} \overline{r_i} & \text{if } \exists\ \overline{r_i} \\ \overline{r_a} & \text{otherwise} \end{cases}$

Plan

Campaign

Epinions dataset[1] extracted by [Richardson2002]:

- "weakly connected": less than 5 friends
- "fairly connected": 5 to 9 friends
- "highly connected": 10 or more friends

Leave-one-out campaign

- One rating at a time

[1] www.epinions.com

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Coverage by actors connectivity

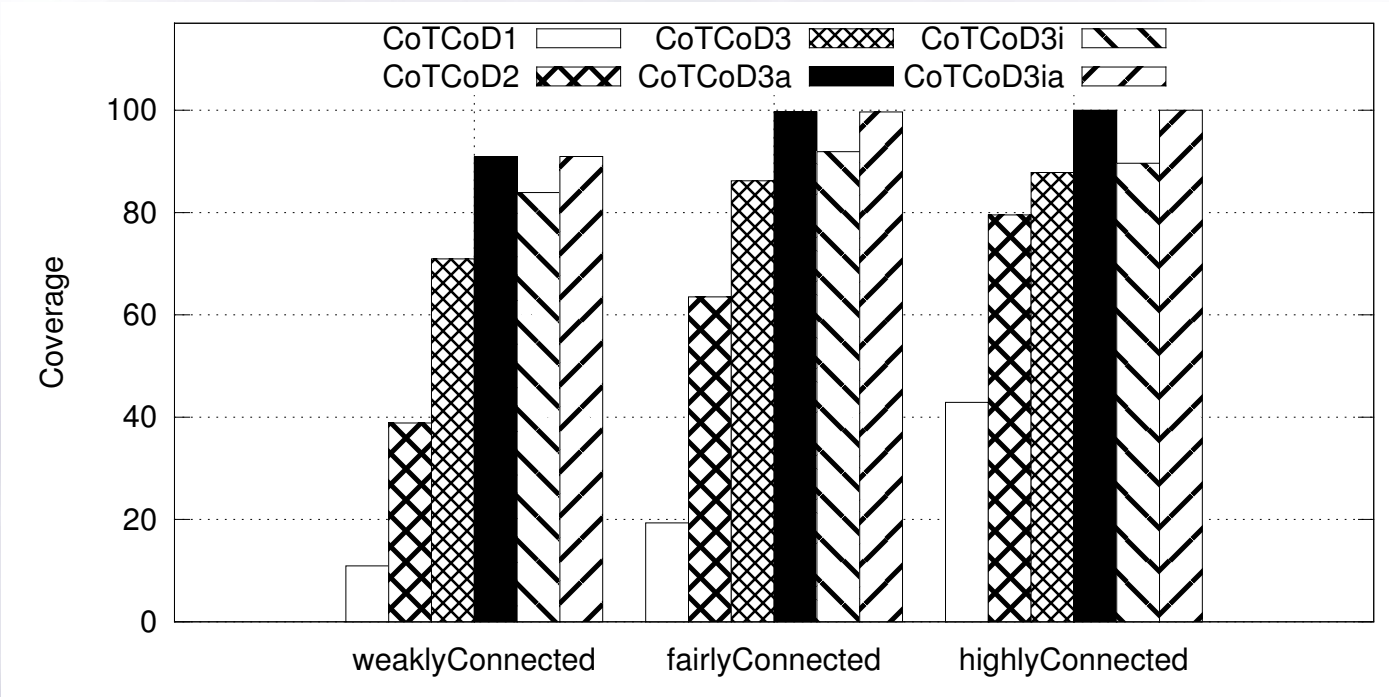

Figure : Coverage of CoTCoDepth scorers

Comparison with existing approaches

Method	Precision	Cov.	F_1	Knowledge
MoleTrust3	0.725	77.25	0.748	extended-local
RandomWalk3	0.682	53.44	0.599	local
CoTCoD3	0.712	77.25	0.741	local
TrustWalker3	0.727	85.99	0.788	local + global
CoTCoD3$_a$	0.723	90.50	0.804	local
CoTCoD3$_{ia}$	0.730	90.56	0.809	local + anonymous

Table : Results for all actors on Epinions

Plan

Conclusion

Local Recommender System

- Only friends share data
- Score propagation
- Users manage their own profiles
- P2P compliant

Features

- Trust and local similarity
- Confidence on scores
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Perspectives

On our recommendation approach

- Content-based
- Extended similarity
- Public profiles (experts)
- ω coefficient depending on the item category

P2P architecture

- Limit network usage (friends subsets)
- Disconnections
- Cache

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Thanks for your attention...

Bibliography

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Campaign

Epinions statistics:

- 47 000 users
- 104 000 items
- 586 000 ratings
- 509 000 trust values

Views:

- "weakly connected": 47 % of actors, 22 % of ratings
- "fairly connected": 11 % of actors, 12 % of ratings
- "highly connected": 18 % of actors, 57 % of ratings

Metrics

- Coverage: proportion of predicted ratings regarding all ratings to predict
- Precision: precision metric based on the RMSE (Root Mean Square Error)
- F1-Measure: combination of the coverage and the precision

$$Precision = 1 - \frac{RMSE}{range}$$

$$\text{with } RMSE = \sqrt{\frac{\sum_{n=1}^{N} (p_n - r_n)^2}{N}}$$

$$F_1 = \frac{2 \times Precision \times Coverage}{Precision + Coverage}$$

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Precision

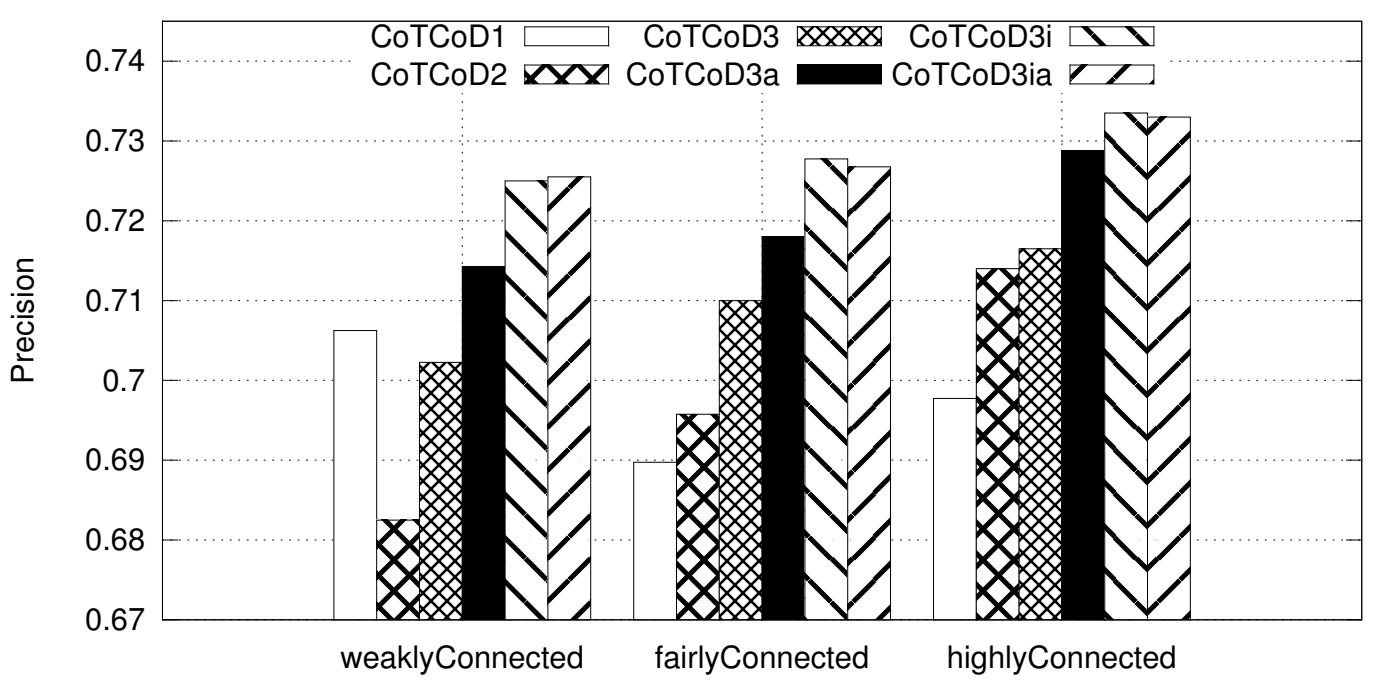


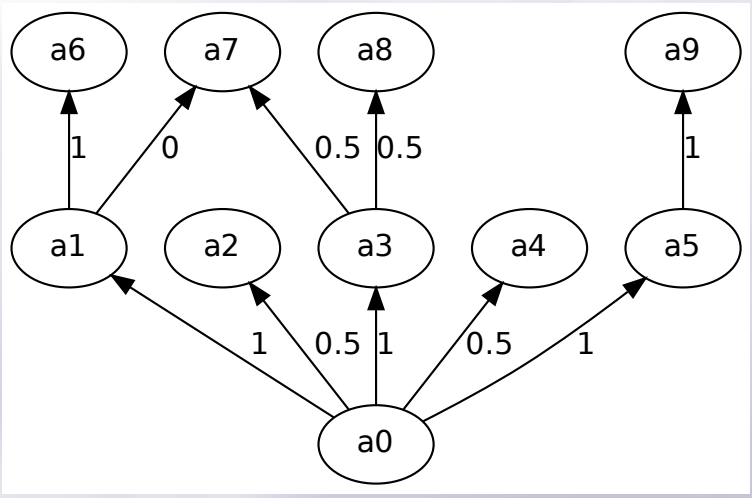
Figure : Precision of CoTCoDepth scorers

Comparison with existing approaches: cold start users

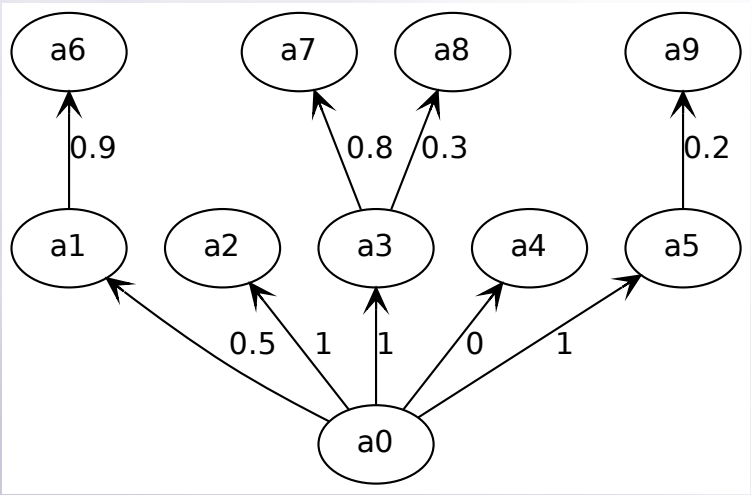
Method	Precision	Cov.	F_1	Knowledge
MoleTrust3	0.708	50.51	0.590	extended-local
RandomWalk3	0.678	37.74	0.485	local
CoTCoD3	0.701	50.51	0.587	local
TrustWalker3	0.678	67.50	0.677	local + global
CoTCoD3$_a$	0.713	65.05	0.681	local
CoTCoD3$_{ia}$	0.724	65.48	0.688	local + anonymous

Table : Results for cold start users on Epinions

ω example



(a) Friends' trust network



(b) Friends' similarity network

Figure : Trust and similarity networks

Default score

$P_{default}$ is the probability to return a defined default score

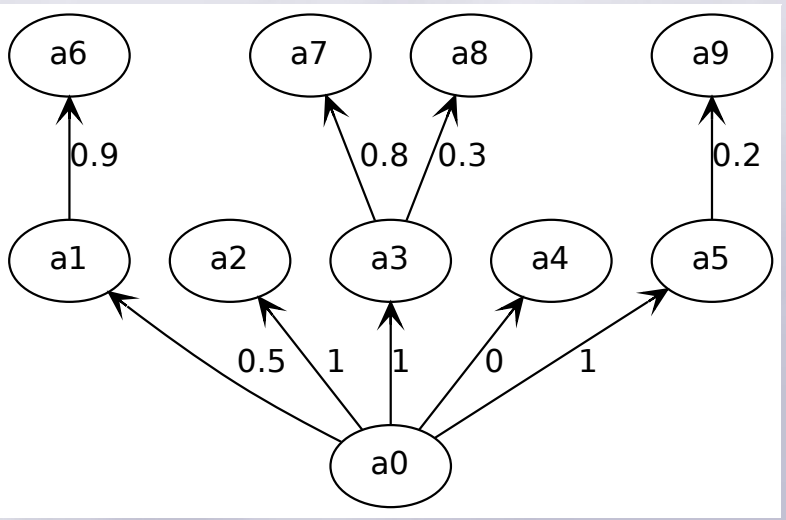
$$P(default(a,i) = \left\{ \begin{array}{c} \overline{r_a} \\ \overline{r_i} \end{array} \right.) = P_{default} \quad (3)$$

$$P(default(a,i) = \perp) = (1 - P_{default}) \quad (4)$$

In our experimentations : $P_{default} = 0.02$

Confidence

$$c_{a,i} = \frac{\sum_{f \in \mathcal{F}^k_{a,i,\omega}} \omega_{a,f} \times c_{f,i}}{|\mathcal{F}^k_{a,i,\omega}|} \qquad \omega^{(c)}_{a,f} = \omega_{a,f} \times c_{f,i}$$



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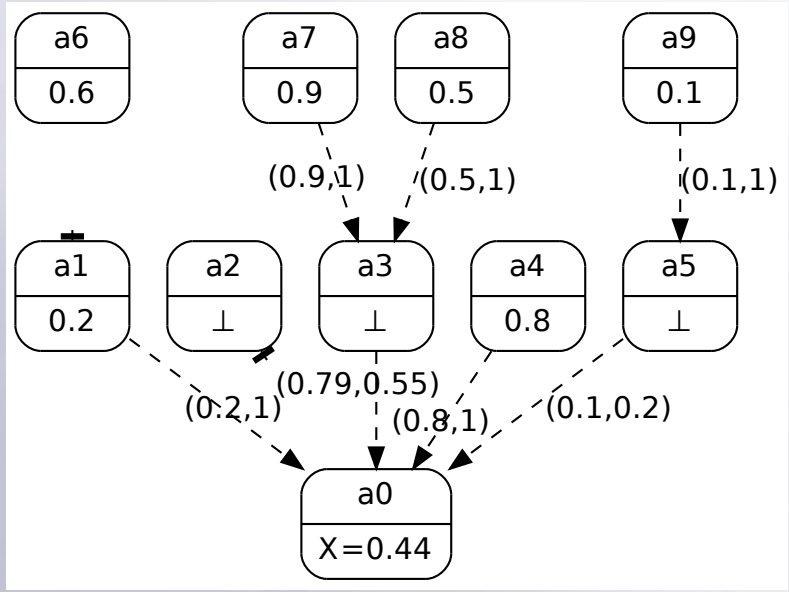

(b) Score propagation

Figure : Confidence Example